Using Weak Separability and Generalized Composite Commodity Theorem in Modeling Ground Beef Demand

Lee L. Schulz
Department of Agricultural Economics
Kansas State University
Manhattan, KS 66506
Phone: 785-532-2113
Fax: 785-532-6925
E-mail: leeschulz@agecon.ksu.edu

Ted C. Schroeder
Department of Agricultural Economics
Kansas State University
Manhattan, KS 66506
Phone: 785-532-4488
Fax: 785-532-6925
Email: tcs@ksu.edu

Tian Xia
Department of Agricultural Economics
Kansas State University
Manhattan, KS 66506
Phone: 785-532-1512
Fax: 785-532-6925
Email: tianxia@agecon.ksu.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011.

The authors would like to acknowledge John Lundeen, National Cattlemen's Beef Association; The Beef Checkoff; and Dave Shepard, Meat Solutions LLC for providing the data.

Introduction

Given the large number of retail food products, consumer food demand and price analysis is always implemented at some level of aggregation and separation. For example, past literature has maintained that meat products are weakly separable from all other goods (e.g., Eales and Unnevehr 1988; Brester and Wohlgenant 1991; Moschini, Moro, and Green 1994; and Kinnucan et al. 1997). Aggregate meat demand models have been effective for analyzing health information (Kinnucan et al. 1997), commodity promotion (Brester and Schroeder 1995), food safety concerns (Piggott and Marsh 2004; Marsh, Schroeder, and Mintert 2004), and numerous other issues. Data aggregation in meat demand work has been largely driven by data availability. That is, typical meat demand studies have relied upon USDA quarterly consumption data aggregated by species (beef, pork, poultry, etc.). With increasing availability of scanner and panel diary data, the data aggregation and separability assumptions have received greater attention (Capps and Love 2002). Data aggregation in demand analysis can mask important details about individual product demand and can result in biased and unreliable elasticity estimates. Consistent aggregation requires that all the properties of consumer behavior will apply to the aggregate behavior (Davis, Lin, and Shumway 2000).

Ground beef is an ideal product to study relative to the issue of data aggregation. Ground beef is differentiated in the retail counter by percentage lean and by product brand. Increased consumer preferences for low-fat ground beef (Brester et al. 1993; Lusk and Parker 2009) has lead retailers to differentiate the product by lean percentage varying from 70% to 100% lean. Branding of retail ground beef has also become common. The National Meat Case Study finds ground beef branding is increasing. Despite rapid development of differentiated ground beef retail products, no meat demand study has been conducted on disaggregated ground beef products. Little is known about the demand elasticities for different ground beef products. Furthermore, the appropriateness of aggregating ground beef into one product for demand analysis has not been studied. Ground beef is an important component of overall beef demand as it represents 48% of retail beef case quantity sold and 37% of total beef sales revenue in 2008 based on Freshlook data. As such, ground beef demand warrants more detailed analysis.

Retail scanner data is a relatively new data collection process that offers accurate volume weighted pricing data revealing what consumers are purchasing and how much they are spending on individual retail products. Scanner data allow significant advances in understanding food product marketing because they enable us to estimate brand and individual product demand models (Cotterill 1994; Capps and Love 2002). Numerous model specification and econometric considerations arise from scanner data use in demand analysis. Access to ground beef scanner data enables us to determine how product brand and lean percentage relate to weak separability and aggregation.

For years, weak separability has been used as justification for aggregating demand data, though it has been assumed more often than tested. If separability conditions were not satisfied, it was considered inappropriate to aggregate. If separability was violated, empirical research had to rely upon disaggregate demand systems which lead to many difficulties in estimation including multicollinearity, degrees of freedom constraints, and computational limitations. Recently, demand analysis has relied upon the Generalized Composite Commodity Theorem (GCCT), proposed by Lewbel (1996), to reduce these problems. The GCCT is an attractive method for determining if aggregation is viable as the conditions for commodity aggregation are more easily met and less restrictive than weak separability. However, the GCCT is not an alternative version of seperability and testing the GCCT is not an alternative test for separability.

The GCCT and separability are two different ways of justifying commodity aggregation (Davis, Lin, and Shumway 2000).

This paper tests for valid aggregation under GCCT and reports estimates of demand elasticities for retail ground beef products. In addition, we present tests for weak separability.

Previous Research and Work Needed

To justify aggregate demand analysis, weak separability is many times imposed or assumed as conducting formal weak separability tests are not feasible. However, imposing weak separability places severe restrictions on the degree of substitutability between goods in different groups (Deaton and Muellbauer 1980). When tests for weak separability are feasible, separability is often rejected (Eales and Unnevehr 1988; Diewart and Wales 1995). According to Davis (1998), there are only three published articles that have tested for weak separability in meat demand in the United States: Eales and Unnevehr (1988); Moschini, Moro, and Green (1994); and Nayga and Capps (1994).

Researchers are beginning to rely more on the GCCT for aggregation because the conditions are more easily met and, as a result, even if commodity aggregation is not justified by separability, it may be justified by the GCCT. The GCCT can accordingly be used to easily validate that one can treat the products in question as a separate group provided that the theorem holds. Limited studies exist examining the relationship between weak separability and GCCT. Davis (1998) used weekly retail meat data from a single firm in Houston, TX covering six different meat species in which weak separability conditions were rejected to determine if aggregation could be based on the GCCT. He found no empirical justification for aggregation of the data for demand estimation. As a result, questions arose regarding the value of using the GCCT for empirical demand estimation.

More encouraging results were provided by Davis, Lin, and Shumway (2000) who used GCCT tests to provide empirical support for many commonly employed aggregation schemes in production data. Another important contribution was the testing framework developed to enable the rather involved procedures required by the GCCT.

Reed, Levedahl, and Hallahan (2004) built upon the existing literature and used the GCCT to test and justify aggregation schemes. From these aggregation schemes they estimated aggregate food demand elasticities, which were reasonably consistent with previous literature. This suggests the use of the GCCT can provide proper aggregation for use in demand analysis. However, they concluded that their aggregation scheme could not be based on weakly separable preferences.

A limited number of studies have focused on demand systems with highly related, but differentiated products. One exception is Capps and Love (2002) who compared elasticities for fruit juices and drinks obtained using demand systems estimated incorporating product aggregates constructed using the GCCT compared with those estimated using multistage budgeting.

In this study, we utilize retail scanner data of branded ground beef with differing lean percentage levels to provide information on appropriate aggregation schemes and determine whether these schemes are consistent with weakly separable preferences. Our study allows us to better understand how consumers make decisions concerning ground beef purchases. For example, do consumers select among various lean percentage levels and/or brand types?

Data

Weekly retail ground beef scanner data were collected by the FreshLook Marketing Group during 2004 through March 2009. FreshLook Marketing Group collects meat department

InfoScan random weight sales data from more than 14,000 retail food stores nationwide. In all, there are approximately 175 retail market areas covered and approximately 68 percent of all U.S. grocery stores captured. Data recorded for each sale included: price, quantity, brand name, and lean percentage level. The data consisted of 64 different ground beef brands that were classified into the following categories: 1) local/regional - distributed within a local or regional geographic area and is owned and controlled by a private company, 2) national - distributed to retail locations nationwide and controlled by the company or the supplier(s) who owns the brand, 3) store - specific to a certain retail store or chain of stores and owned and controlled by the retail grocery store or chain of stores, and 4) other – a product without a brand name on the label.

Ground beef is grouped by Freshlook into five different lean percentage categories: 1) 70-77%, 2) 78-84%, 3) 85-89%, 4) 90-95%, and 5) 96-100% lean. Data on store brands of 96-100% lean was not available. This is because within the ground beef market there are few transactions of this leanness level. Table 1 provides the shares for the lean percentage levels and brand types of ground beef.

There are 19 ground beef products (4 brand types × 5 lean percentages less the store brand 96-100% lean). The GCCT tests conducted involved three possible subsets of these products. Table 2 identifies the three groups of products we tested for consistency with the GCCT. Common letters in each aggregation column indicate which products were hypothesized to be valid aggregates in a particular group. Groups A-E were aggregated based on lean percentage level and groups F-I were aggregated based on brand type. Group J aggregates all ground beef products into a single product.

We use these groupings of the disaggregated ground beef products to test for weak separability. Utility tree 1 is partitioned based on product leanness; therefore, there are five separable groups (70-77%, 78-84%, 85-89%, 90-95%, and 96-100%). Utility tree 2 is partitioned based on brand type with four separable groups (local/regional, national, store, and other).

Methods

Generalized Composite Commodity Theorem Tests

The GCCT is a stochastic theory of aggregation over various products. See Lewbel (1996) for a detailed development of the theory and an application. Davis (1998), Davis, Lin, and Shumway (2000), and Capps and Love (2002) have applied the GCCT to various demand and production data.

Lewbel (1996) finds that commodities can be reasonably aggregated when "changes in the relative prices of the goods are unrelated to the general rate of inflation of the group" (p. 525). Empirical testing requires determining whether relative individual commodity prices (ρ_i) are statistically independent of an aggregate price index for that group (P_I). First, we computed an aggregate group price index for each group I. For aggregation test groups 1, 2, and 3 the group price indices were with respect to lean percentage level, brand type, and all products, respectively. Next, relative prices were calculated as: $\rho_i = r_i - R_I$, where $r_i = lnp_i$ and $R_I = lnP_I$. The first step was to test the data for unit roots and if applicable cointegration or correlation. The test procedure employed was: 1) if ρ_i and R_I are both stationary then a test for independence such as a correlation test is done, 2) if ρ_i and R_I are both nonstationary then a test for independence such as a cointegration test is done, 3) if ρ_i is stationary and R_I is nonstationary then aggregation is possible, and 4) if ρ_i is nonstationary and R_I is stationary then aggregation is possible. A result of no correlation or cointegration suggests the series are independent and can be aggregated. In cases (3) and (4), where one series is stationary (either ρ_i or R_I) and the other is nonstationary, no test for independence is required because under the algebra of cointegration (Granger and Hallman 1989) two series cannot be cointegrated if one is stationary and the other is nonstationary.

Tables 3, 4, and 5 summarize the GCCT tests for the relative prices and group prices under the differing aggregation schemes. Following Lewbel (1996), two stationary tests were conducted: the Augmented Dickey-Fuller (ADF) with a null of nonstationarity and the Kwaitkowski, Phillips, Schmidt, and Shin (KPSS) tests with a null of stationarity. Having two tests introduces the possibility of conflicting results. Therefore, inferences based on the joint confirmation hypothesis (JCH) of a unit root were used when the ADF and KPSS tests conflicted (Silvestre, Rossello, and Ortuno 2001). In all three test groups, the group price indices were nonstationary and 14 (test group 1), 13 (test group 2), and 14 (test group 3) of the relative prices were nonstationary; consequently, where relative prices were nonstationary aggregation rested on cointegration tests alone and where relative prices were stationary aggregation was deemed possible. Engle Granger tests were used to test for cointegration with each individual test failing to reject the null of spurious regression (not cointegrated). Because none of the individual tests rejected the null there was no need to perform a family-wise test as in previous studies of GCCT testing (e.g., Davis, Lin, and Shumway 2000; Reed, Levedahl, and Hallahan 2004). Results indicate that demand elasticities for each of the aggregation schemes accurately reflect the elasticities for the products that consumers actually purchase (Lewbel 1996). That is we can justify estimating a demand system having five different lean percentage levels aggregated across brand types, a demand system having four different brand types with lean percentages aggregated, or estimating ground beef as a single commodity aggregated across brand types and lean percentages.

Rotterdam Model

The absolute price version of the Rotterdam model was used. See Theil (1980) for a detailed development of the Rotterdam model. This specification is chosen because it is based on consumer demand theory (i.e., allow imposition of symmetry and homogeneity restrictions) and is sufficiently flexible to capture variations in consumer behavior, especially demand elasticities (Brester and Wohlgenant 1991; Capps and Love 2002). The *i*th equation of our estimated model is given by:

$$(1) \qquad w_i \Delta \ln(q_i) = \theta_i \Delta \ln(Q) + \sum_{j=1}^{n} \pi_{ij} \Delta \ln(p_j) + v_i,$$

where w_i is the budget share of the *i*th product (time subscripts (t) on each variable are omitted for convenience); Δ is the standard first-difference operator [e.g., $\Delta \ln Y_t = \ln(Y_t) - \ln(Y_{t-1})$]; q_i is consumption of the *i*th product; p_j is the price of the *j*th product; $\Delta \ln(Q)$ is the Divisia volume index [$\sum_{i=1}^{n} w_i \Delta \ln(q_i)$]; v_i is a random error term; and θ_i and π_{ij} are parameters to be estimated.

To avoid singularity in the estimated error variance-covariance matrix we omit one share equation from the empirical model. The parameters of this omitted equation are recovered using the adding-up restrictions. In addition, symmetry and homogeneity restrictions are imposed as maintained assumptions to ensure the demand model is consistent with economic theory. Adding-up restrictions are:

$$(2) \qquad \sum_{i=1}^{n} \theta_i = 1 \text{ and } \sum_{i=1}^{n} \pi_{ij} = 0.$$

Homogeneity and symmetry are imposed, respectively, by:

$$(3) \qquad \sum_{j=1}^{n} \pi_{ij} = 0 \text{ and } \pi_{ij} = \pi_{ji}.$$

Although the Rotterdam model is not derived from an underlying utility or expenditure function, it satisfies the integrability conditions when homogeneity and symmetry are imposed (Deaton and MuellBauer 1980; Capps and Love 2002). Each system is estimated using iterated seemingly unrelated regression, allowing for the correlation between errors from different equations (i.e., covariance matrix of the entire system is not diagonal). Error terms are expected to be correlated as we are estimating demands for related products.

Equations (1) - (3) generate compensated price elasticities given by:

(4) $$\varepsilon_{ij} = \frac{\pi_{ij}}{w_i}.$$

The expenditure elasticity is represented by:

(5) $$\eta_i = \frac{\theta_i}{w_i}.$$

The Rotterdam model's coefficient estimates are of limited value except for calculating elasticities. Therefore, we focus on the model's estimated elasticities (as shown above). A 95% confidence interval for each mean elasticity estimate was calculated using the delta method. The delta method estimates the variance of a nonlinear function of two or more random variables by taking a first-order Taylor series expansion around the mean value of the variable and calculating the variance on that newly created random variable (Greene 2003). The delta estimate of the variances of the compensated price and expenditure elasticities is given, respectively, by:

(6) $$\mathrm{var}(\varepsilon_{ij}) = \frac{1}{\bar{w}_i^2}\mathrm{var}(\hat{\pi}_{ij}),$$

(7) $$\mathrm{var}(\eta_i) = \frac{1}{\bar{w}_i^2}\mathrm{var}(\hat{\theta}_i).$$

Once the variance of the elasticity estimate is calculated, confidence intervals can be calculated in the standard way.

Separability Tests

If separability of preferences holds, ground beef can be partitioned into groups so that preferences within groups can be described independently of quantities in other groups, which implies that we can have a sub-utility function for each group and that the values of these sub-utilities combine to give total utility (Deaton and MuellBauer 1980). Separability can also be used to justify commodity aggregation; whereby, goods belonging to a group may be aggregated if the direct utility function is weakly separable (Nayga and Capps 1994). Separability is widely imposed in empirical demand studies to reduce the number of estimated parameters. Few studies, with the exception of Pudney (1981), Eales and Unnevehr (1988), and Nayga and Capps (1994), involve testing separability within groups of meat products. Here we test for weak separability on disaggregated ground beef products. Because the focus is on the ground beef market, weak separability from all other meat and nonmeat products is implicitly imposed.

We utilize the testing framework of Moschini, Moro, and Green (1994). Under the assumption of weak separability of the direct utility function, the ratio of cross-price elasticities of two products within the same group (r), with respect to a third product in another group (s), is equal to the ratio of their expenditure elasticities.

For the Rotterdam model, this result implies a nonlinear restriction on the parameters π_{ij}, where $i, k \in r$ and $j \in s$. This restriction is given by:

(8) $$\frac{\pi_{ij}}{\pi_{kj}} = \frac{\theta_i}{\theta_k}.$$

The Rotterdam model is separability-flexible for the purpose of modeling weak separability as these separability restrictions hold not only locally, but also globally (Moschini, Moro, and Green 1994).

We employ likelihood ratio procedures to conduct the separability tests.[1] To accommodate the likelihood ratio test, we impose 134 (utility tree 1) and 129 (utility tree 2) nonlinear separability restrictions in addition to the classical homogeneity and symmetry restrictions (171).

According to Laitinen (1978) and Meisner (1979) tests of restrictions in large demand systems are biased toward rejection; thus we make a size correction. The corrected likelihood ratio is given by (Moschini, Moro, and Green):

$$LR_0 = LR\left[\frac{MT - \frac{1}{2}(N_{UR} - N_R) - \frac{1}{2}M(M+1)}{MT}\right] \tag{9}$$

where LR is the test statistic of the conventional likelihood ratio test, M is the number of equations, T is the number of time series observations, N_{UR} is the number of parameters of the unrestricted model, and N_R is the number of parameters in the restricted (separable) model.

Results

Table 6 presents the calculated compensated own- and cross-price and expenditure elasticities for each lean percentage level of ground beef aggregated across brand types. The own-price elasticities are all negative and statistically significant at the 0.05 level. We are unaware of any other study that has estimated price elasticities for individual ground beef lean percentage products. Previous estimates are available for aggregate ground beef elasticities. For example, compensated elasticity estimates for ground beef include Brester and Wohlgenant (1991) with an estimate of -1.02; Nayga and Capps (1994) with an estimate of -1.22; and Coffey, Schroeder, and

[1] The separability restrictions to be tested are nonlinear parametric restrictions. To test parametric restrictions it is common to use the Wald test; however, the Wald testing procedure has a severe drawback when testing for weak separability. The Wald test lacks variance to the specification of nonlinear restrictions (Gregory and Veall 1985) and is not invariant with respect to the choice of nonredundant separability restrictions (Moschini, Moro, and Green 1994).

Marsh (2010) with an estimate of -1.08. Our elasticity estimates range from -1.29 to -0.44, being inelastic for 70-77%, 78-84%, and 85-89% lean and elastic for 90-95% and 96-100% lean.

The more inelastic demand for the lower lean percentage ground beef products relative to leaner products suggests that consumer purchases of the cheaper, less lean, ground beef products are less responsive to own-price changes. Based on hedonic modeling, White (2010) found that 90% and higher lean ground beef had a retail price premium of a $1.00/lb or more relative to less than 85% lean products. We hypothesize that less lean ground beef is purchased by relatively lower-income consumers compared to the more expensive high lean product. Thus, less lean ground beef products may be more of a necessity for consumers that regularly purchase the product, compared to those who buy the leaner product.

All of the statistically significant cross-price elasticities are positive, as is expected for substitute products. The two lean percentages with the largest market shares are 70-77% (0.40 share) and 90-95% (0.23 share). These two products tend to be the strongest substitutes for the others. Expenditure elasticities range from 1.22 for 70-77% to 0.48 for 96-100% lean. The 96-100% lean product is a niche market having only a 0.02 market share among the five products. The fact that the lowest lean product has the largest income elasticity again suggests that lower-income, budget-constrained consumers may represent a large share of the consumers purchasing the product.

Table 7 presents the calculated compensated own- and cross-price and expenditure elasticities for each brand type of ground beef aggregated across lean percentage level. The own-price elasticities for brands are negative as expected. Our elasticity estimates range from -4.55 to -0.13, being inelastic for other brand types and elastic for local/regional, national, and store brand types. An implied ranking of consumer's price sensitivity to own-price is: (1)

local/regional, (2) store, (3) national, and (4) other. This tendency suggests consumers are more sensitive to price increases for less commonly known brands and less sensitive to price increases for well-known brands (i.e., national). There are no published demand elasticities for branded ground beef to compare to our estimates. Richards and Padilla (2009) estimated elasticities that included fast food restaurants that specialize in hamburgers including McDonalds, Burger King, and Wendy's. They found elasticities for brand choice ranged from -2.9 to -3.8 for these three firms and for purchase quantity once in the establishment ranged from -1.6 to -1.9.

As expected, all the brand type expenditure elasticities are positive and consistent with economic intuition. The local/regional brand expenditure elasticity was not significant at the 5% level. All the cross-price elasticities are positive indicating the brands are all substitutes as is expected with such closely related products. The *Other* brand type (0.94 share) includes mostly unbranded product that is also relatively cheap compared to the branded products. As such, generic ground beef may represent a staple or necessity for budget-constrained households. In contrast, branded ground beef products have strong substitutes of other brands or the cheaper generic product.

Results of the separability tests are shown in table 8. Using the uncorrected and corrected likelihood test statistics, the hypothesis of weak separability of utility tree 1 and utility tree 2 (table 2) is rejected at the 1% significance level. The implication of this finding is that consumers neither select among various brands of a particular lean percentage nor select among various lean percentages of a particular brand type. Hence, in analyzing the demand for ground beef, researchers may not focus solely on the demand for a particular lean percentage or a particular brand type. Researchers must consider the demands for all types of ground beef simultaneously. The importance of the GCCT is that even if commodity aggregation is not justified by separability, it may be justified by the GCCT. That is precisely the case here. The GCCT verifies that lean percentage levels and brand types of ground beef are valid aggregates for demand system estimation.

Disaggregated models are preferable in demand analysis as they allow one to test for appropriateness of aggregation and account for the full information of the system. However, disaggregated models can have problems in estimation including degrading multicollinearity, degrees of freedom constraints, and computational limitations. Furthermore, if measurement error exists, misspecification problems can be exacerbated for disaggregated models because the misspecification affects the whole system. In contrast, when aggregates are estimated misspecification can be less burdensome as the impacts may only affect a product or group of products within the model. We estimated a disaggregated demand system with 19 ground beef products (4 brand types × 5 lean percentages less the store brand 96-100% lean) and found the system to be sensitive to model specification. In the estimation of the disaggregated model, results were inconsistent with the choice of the $n-1$ equations included in the model. However, the aggregate estimates of lean percentage level (table 6) and brand type (table 7) were invariant to any choice of equation omitted in estimation. Therefore, the GCCT appears to justify aggregation from an econometric standpoint.

Conclusions and Implications

In this study, we utilized retail scanner data of branded ground beef with differing lean percentage levels to provide information on appropriate aggregation schemes and determine whether these schemes are consistent with weakly separable preferences. There is empirical justification for the aggregation of ground beef for this data based on the Generalized Composite Commodity Theorem. We justified estimating a demand system having five different lean percentage levels aggregated across brand types, a demand system having four different brand types with lean percentages aggregated, or estimating ground beef as a single commodity aggregated across brand types and lean percentages. There was no apparent empirical justification for the aggregation of ground beef for this data based on weak separability. This shows the importance of the GCCT in that even if commodity aggregation is not justified by separability, it may be justified by the GCCT. This was precisely the case here. The GCCT verifies that lean percentage levels and brand types of ground beef are valid aggregates for demand system estimation.

Ground beef is an important component of overall beef demand. Sales data from FreshLook Marketing confirms ground beef's share was 48% of retail beef case quantity sold and 37% of total beef sales revenue in 2008. This study provided the first estimated price and income elasticities for individual ground beef lean percentage and branded products. These estimates provide better understanding of how consumers make decisions concerning ground beef purchases.

References

Brester, G.W., L. Pascale, B.K. Goodwin, and M.C. Hunt. 1993. "Quantifying the Effects of New Product Development: The Case of Low-Fat Ground Beef." *Journal of Agricultural and Resource Economics.* 18.2:239-250.

Brester, G.W. and T.C. Schroeder. 1995. "The Impacts of Brand and Generic Advertising on Meat Demand." *American Journal of Agricultural Economics*. 77(November):969-979.

Brester, G.W. and M.K. Wohlgenant. 1991. "Estimating Interrelated Demands for Meats Using New Measures for Ground Beef and Table Cut Beef." *American Journal of Agricultural Economics*. 72(November):1182-1194.

Capps Jr., O and H.A. Love. 2002. "Econometric Considerations in the Use of Electronic Scanner Data to Conduct Consumer Demand Analysis." *American Journal of Agricultural Economics*. 84.3(August):807-816.

Coffey, B.K., T.C. Schroeder, and T.L. Marsh. 2010. "Disaggregated Household Meat Demand with Censored Data." *Applied Economics* iFirst. 1-21.

Cotterill, R.W. 1994. "Scanner Data: New Opportunities for Demand and competitive Strategy Analysis." *Agricultural and Resource Economics Review*. 23(October):125-129.

Davis, G.C. 1998. "Testing Aggregation Without Separability in Meat Demand: An Investigation of the Generalized Composite Commodity Theorem." Paper presented at American Agricultural Economics Association Annual Meeting. Salt Lake City Utah, 2-5 August.

Davis, G.C., N. Lin, and C.R. Shumway. 2000. "Aggregation Without Separability: Tests of the United States and Mexican Agricultural Production Data." *American Journal of Agricultural Economics*. 82(2000):214-230.

Deaton, A.S. and J. Muellbauer. *Economics and Consumer Behavior*. Cambridge: Cambridge University Press, 1980.

Dickey, D.A., and W.A. Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of American Statistical Association*. 74:427-431.

Diewart, W.E. and T.J. Wales. 1995. "Flexible Functional Forms and Tests for Homogeneous Separability." *Journal of Econometrics*. 67:259-302.

Eales, J.S. and L.J. Unnevehr. 1988. "Demand for Beef and Chicken Products: Separability and Structural Change." *American Journal of Agricultural Economics*. 70(August):521-532.

Granger, C.W.J., and J. Hallman. "The Algebra of I(1)." Finance and Economics Discussion Series, paper 45, Division of Research and Statistics, Federal Reserve Board, Washington DC, 1989.

Greene, W.H. *Econometric Analysis*, 5th edition. Upper Saddle River, New Jersey: Prentice-Hall, Inc., 2003.

Gregory, A. and M. Veall. 1985. “Formulating Wald Tests on Nonlinear Restrictions.” *Econometrica* 53:1465-1468.

Kinnucan, H.W., H. Xiao, C. Hsia, and J. Jackson. 1997. “Effects of Health Information and Generic Advertising on U.S. Meat Demand.” *American Journal of Agricultural Economics*. 79.1:13-23.

Kwaitkowski, D., P.C.B. Phillips, P. Schmidt, and Y. Shin. 1992. “Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root.” *Journal of Econometrics.* 54:159-178.

Laitinen, K. 1978. “Why is Demand Homogeneity So Often Rejected?” *Economic Letters.* 1.3: 187-191.

Lewbel, A. 1996. “Aggregation Without Separability: A Generalized Composite Commodity Theorem.” *The American Economic Review*. 86.3(June):524-542.

Lusk, J.L. and N. Parker. 2009. “Consumer Preferences for Amount and Type of Fat in Ground Beef.” *Journal of Agricultural and Applied Economics*. 41.1(April):75-90.

MacKinnon, J.G. 1996. “Numerical Distribution Functions for Unit Root and Cointegration Tests.” *Journal of Applied Econometrics.* 11:601-618.

Marsh, T.L., T.C. Schroeder, and J. Mintert. 2004. “Impacts of Meat Product Recalls on Consumer Demand in the USA.” *Applied Economics.* 36:897-909.

Meisner, J.F. 1979. “The Sad fate of the Asymptotic Slutsky Symmetry Test for Large Systems.” *Economic Letters.* 2.3:231-233.

Moschini, G., D. Moro, and R. Green. 1994. “Maintaining and Testing Separability in Demand Systems.” *American Journal of Agricultural Economics*. 76(February):61-73.

Nayga, R.M., Jr. and O. Capps, Jr. 1994. “Tests of Weak Separability in Disaggregated Meat Products.” *American Journal of Agricultural Economics*. 76(November):800-808.

Piggott, N.E. and T.L. Marsh. 2004. “Does Food Safety Information Impact U.S. Meat Demand?” *American Journal of Agricultural Economics.* 86.1(February):154-174.

Pudney, S. 1981. “An Empirical Method of Approximating the Separable Structure of Consumer Preferences.” *Review of Economic Studies.* 48:561-77.

Reed, A.J., J.W. Levedahl, and C. Hallahan. 2004. “The Generalized Composite Commodity Theorem and Food Demand Estimation.” Paper presented at the American Agricultural Economics Association Annual Meeting. Denver Colorado, 1-4 August.

Richards, T.J. and L. Padilla. 2009. “Promotion and Fast Food Demand.” *American Journal of Agricultural Economics.* 9.1(February):168-183.

Silvestre, J.L.C., A. S. Rossello, and M.A. Ortuno. 2001. “Unit Root and Stationarity Tests’ Wedding.” *Economics Letters.* 70:1-8.

Theil, *H. The System-Wide Approach to Microeconomics.* Chicago: The University of Chicago Press, 1980.

White, K.L. 2010. “What is the Future of Brand Name Beef: A Price Analysis of Branding Incentives and Other Attributes for Retail Beef using Sales Scanner Data.” Unpublished MS Thesis, Kansas State University.

Table 1. Shares

Product	Share	Product	Share
70 - 77%	0.40	Local/Regional	0.01
78 - 84%	0.21	National	0.03
85 - 89%	0.14	Store	0.02
90 - 95%	0.23	Other	0.94
96 - 100%	0.02		

Table 2. Possible Test Groups/Utility Trees

	Commodity		Aggregation Test Groups (Utility Tree)[a]		
Number	Brand	Lean Level	1	2	3
1	Local/Regional	70 - 77%	A	F	J
2	National	70 - 77%	A	G	J
3	Store	70 - 77%	A	H	J
4	Other	70 - 77%	A	I	J
5	Local/Regional	78 - 84%	B	F	J
6	National	78 - 84%	B	G	J
7	Store	78 - 84%	B	H	J
8	Other	78 - 84%	B	I	J
9	Local/Regional	85 - 89%	C	F	J
10	National	85 - 89%	C	G	J
11	Store	85 - 89%	C	H	J
12	Other	85 - 89%	C	I	J
13	Local/Regional	90 - 95%	D	F	J
14	National	90 - 95%	D	G	J
15	Store	90 - 95%	D	H	J
16	Other	90 - 95%	D	I	J
17	Local/Regional	96 - 100%	E	F	J
18	National	96 - 100%	E	G	J
19	Other	96 - 100%	E	I	J

[a] In each test group/utility tree, all products with the same letter are assumed to belong to the same group. Products with different letters are assumed to be weakly separable.

Table 3. GCCT Test Results for Test Group 1

Group and Relative Prices	Share (%)	ADF Test H_0: *I(1)*[a]	KPSS Test H_0: *I(0)*[b]	*I(0)* or *I(1)*?[c]	Engle-Granger Test H_0: Not Cointegrated[d]
		τ_t	η_t		T_k
$R(70-77\%)$		-2.306 (7)	0.326 (5)*	*I(1)*	
$\rho(Local/Regional)$	1.22	-2.491 (8)	0.570 (5)*	*I(1)*	-2.982 (4)
$\rho(National)$	0.72	-3.411 (9)*	0.254 (5)*	*I(0)* (JCH)	*NC*
$\rho(Store)$	1.78	-3.420 (6)*	0.252 (5)*	*I(0)* (JCH)	*NC*
$\rho(Other)$	96.28	-2.826 (4)	0.331 (5)*	*I(1)*	-2.809 (4)
$R(78-84\%)$		-2.945 (5)	0.191 (5)*	*I(1)*	
$\rho(Local/Regional)$	0.65	-2.570 (6)	0.281 (5)*	*I(1)*	-2.153 (6)
$\rho(National)$	1.80	-1.683 (6)	0.708 (5)*	*I(1)*	-1.734 (6)
$\rho(Store)$	1.98	-2.965 (11)	0.582 (5)*	*I(1)*	-3.265 (10)
$\rho(Other)$	95.56	-0.718 (6)	0.831 (5)*	*I(1)*	-0.437 (6)
$R(85-89\%)$		-2.759 (6)	0.277 (5)*	*I(1)*	
$\rho(Local/Regional)$	0.32	-4.634 (3)*	0.399 (5)*	*I(0)* (JCH)	*NC*
$\rho(National)$	4.44	-3.320 (10)*	0.134 (5)*	*I(1)* (JCH)	-2.686 (10)
$\rho(Store)$	9.81	-1.519 (7)	0.557 (5)*	*I(1)*	-1.975 (7)
$\rho(Other)$	85.44	-1.702 (7)	0.505 (5)*	*I(1)*	-1.934 (7)
$R(90-95\%)$		-2.618 (11)	0.433 (5)*	*I(1)*	
$\rho(Local/Regional)$	0.29	-1.370 (4)	0.441 (5)*	*I(1)*	-1.422 (4)
$\rho(National)$	5.53	-2.650 (11)	0.469 (5)*	*I(1)*	-2.263 (11)
$\rho(Store)$	4.23	-3.128 (4)	0.360 (5)*	*I(1)*	-2.933 (8)
$\rho(Other)$	89.96	-2.698 (10)	0.604 (5)*	*I(1)*	-2.427 (9)
$R(96-100\%)$		-2.558 (10)	0.663 (5)*	*I(1)*	
$\rho(Local/Regional)$	6.49	-10.898 (1)*	0.122 (5)*	*I(0)* (JCH)	*NC*
$\rho(National)$	31.25	-3.750 (8)*	0.087 (5)*	*I(0)*	*NC*
$\rho(Other)$	62.26	-2.974 (9)	0.185 (5)*	*I(1)*	-3.235 (7)
10% critical values		-3.130	0.119	(-3.391, 0.114)	-5.727

Asterisk (*) denotes rejection of the null at the 0.10 significance level.

[a] The test statistics (τ_t) of the null hypothesis of *I(1)* are the augmented Dickey-Fuller (1979) (ADF) *t*-statistics of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by *R 2.10.1*.

[b] The test statistics (η_t) of the null hypothesis of *I(0)* are the Kwaitkowski, Phillips, Schmidt, and Shin (1992) (KPSS) *t*-statistics. The *t*-statistics are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend, and the error variance estimator is a Bartlett kernel weighted-sum of auto-covariances, with the automatic bandwidth parameter reported in parenthesis.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a Unit Root are used when the ADF and KPSS tests conflict (Silvestre, Rossello, and Ortuno 2001). The joint critical values of (-3.391, 0.114) represent the critical values for 300 observations for the ADF and the KPSS with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than -3.391 and the value of the KPSS statistic is less (greater) than 0.114 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.

[d] The test statistics (T_k) of the null hypothesis that the *k*th relative price and the vector of composite group prices are not cointegrated are augmented Dickey Fuller tests of *I(1)* residuals from regressing the *k*th relative price on each of the four integrated group price indices. The number of lagged first difference residuals included (in the residual regression) is reported in parenthesis, and is determined by *R* 2.10.1. The 0.10 critical values reported for the individual tests are based on 273 observations and eleven integrated explanatory variables, so that *k*=12 in MacKinnon (1996).

Table 4. GCCT Test Results for Test Group 2

Group and Relative Prices	Share (%)	ADF Test H_0: *I(1)*[a]	KPSS Test H_0: *I(0)*[b]	*I(0)* or *I(1)*?[c]	Engle-Granger Test H_0: Not Cointegrated[d]
		τ_t	η_t		T_k
$R(Local/Regional)$		-2.367 (9)	0.617 (5)*	*I(1)*	
$\rho(70 - 77\%)$	52.90	-2.650 (7)	0.423 (5)*	*I(1)*	-2.413 (7)
$\rho(78 - 84\%)$	15.32	-2.993 (6)	0.278 (5)*	*I(1)*	-2.081 (6)
$\rho(85 - 89\%)$	4.58	-3.691 (4)*	0.595 (5)*	*I(0)* (JCH)	*NC*
$\rho(90 - 95\%)$	7.06	-1.178 (7)	0.558 (5)*	*I(1)*	-1.307 (11)
$\rho(96 - 100\%)$	20.15	-2.807 (9)	0.563 (5)*	*I(1)*	-2.575 (10)
$R(National)$		-2.264 (9)	0.387 (5)*	*I(1)*	
$\rho(70 - 77\%)$	8.35	-3.577 (4)*	0.261 (5)*	*I(1)*	*NC*
$\rho(78 - 84\%)$	11.44	-1.427 (10)	0.736 (5)*	*I(0)* (JCH)	-2.068 (10)
$\rho(85 - 89\%)$	17.27	-3.158 (5)*	0.210 (5)*	*I(1)*	-3.021 (8)
$\rho(90 - 95\%)$	36.85	-1.586 (11)	0.419 (5)*	*I(1)* (JCH)	-1.706 (11)
$\rho(96 - 100\%)$	26.09	-1.685 (10)	0.529 (5)*	*I(1)*	-1.813 (8)
$R(Store)$		-1.662 (11)	0.652 (5)*	*I(1)*	
$\rho(70 - 77\%)$	20.88	-2.537 (5)	0.227 (5)*	*I(1)*	-1.927 (4)
$\rho(78 - 84\%)$	12.63	-3.441 (10)*	0.107 (5)	*I(0)*	*NC*
$\rho(85 - 89\%)$	38.25	-3.834 (4)*	0.189 (5)*	*I(0)* (JCH)	*NC*
$\rho(90 - 95\%)$	28.23	-1.882 (11)	0.663 (5)*	*I(1)*	-2.915 (8)
$R(Other)$		-2.347 (7)	0.464 (5)*	*I(1)*	
$\rho(70 - 77\%)$	41.43	-2.015 (8)	0.335 (5)*	*I(1)*	-2.150 (11)
$\rho(78 - 84\%)$	22.35	-3.097 (11)	0.615 (5)*	*I(1)*	-3.465 (7)
$\rho(85 - 89\%)$	12.24	-4.328 (7)*	0.165 (5)*	*I(0)* (JCH)	*NC*
$\rho(90 - 95\%)$	22.07	-3.908 (11)*	0.064 (5)	*I(0)*	*NC*
$\rho(96 - 100\%)$	1.91	-1.830 (8)	0.662 (5)*	*I(1)*	-2.618 (11)
10% Critical Value		-3.130	0.119	(-3.391, 0.114)	-5.727

Asterisk (*) denotes rejection of the null at the 0.10 significance level.

[a] The test statistics (τ_t) of the null hypothesis of *I(1)* are the augmented Dickey-Fuller (1979) (ADF) *t*-statistics of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by *R 2.10.1*.

[b] The test statistics (η_t) of the null hypothesis of *I(0)* are the Kwaitkowski, Phillips, Schmidt, and Shin (1992) (KPSS) *t*-statistics. The *t*-statistics are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend, and the error variance estimator is a Bartlett kernel weighted-sum of auto-covariances, with the automatic bandwidth parameter reported in parenthesis.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a Unit Root are used when the ADF and KPSS tests conflict (Silvestre, Rossello, and Ortuno 2001). The joint critical values of (-3.391, 0.114) represent the critical values for 300 observations for the ADF and the KPSS with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than -3.391 and the value of the KPSS statistic is less (greater) than 0.114 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.

[d] The test statistics (T_k) of the null hypothesis that the *k*th relative price and the vector of composite group prices are not cointegrated are augmented Dickey Fuller tests of *I(1)* residuals from regressing the *k*th relative price on each of the four integrated group price indices. The number of lagged first difference residuals included (in the residual regression) is reported in parenthesis, and is determined by *R* 2.10.1. The 0.10 critical values reported for the individual tests are based on 273 observations and eleven integrated explanatory variables, so that *k*=12 in MacKinnon (1996).

Table 5. GCCT Test Results for Test Group 3

Group and Relative Prices	Share (%)	ADF Test H_0: *I(1)*[a]	KPSS Test H_0: *I(0)*[b]	*I(0)* or *I(1)*?[c]	Engle-Granger Test H_0: Not Cointegrated[d]
		τ_t	η_t		T_k
$R(All\ Commodities)$		-2.332 (7)	0.475 (5)*	*I(1)*	
ρ(Local/Regional 70 − 77%)	0.48	-3.116 (4)	0.541 (5)*	*I(1)*	-3.201 (4)
ρ(Local/Regional 78 − 84%)	0.14	-2.202 (6)	0.217 (5)*	*I(1)*	-2.143 (6)
ρ(Local/Regional 85 − 89%)	0.04	-4.767 (3)*	0.420 (5)*	*I(0)* (JCH)	*NC*
ρ(Local/Regional 90 − 95%)	0.06	-1.526 (4)	0.454 (5)*	*I(1)*	-1.486 (4)
ρ(Local/Regional 96 − 100%)	0.18	-5.652 (5)*	0.224 (5)*	*I(0)* (JCH)	*NC*
ρ(National 70 − 77%)	0.28	-3.161 (9)*	0.269 (5)*	*I(1)* (JCH)	-3.647 (8)
ρ(National 78 − 84%)	0.39	-1.693 (6)	0.621 (5)*	*I(1)*	-1.781 (6)
ρ(National 85 − 89%)	0.59	-3.292 (8)*	0.127 (5)*	*I(1)* (JCH)	-3.141 (8)
ρ(National 90 − 95%)	1.25	-2.989 (11)	0.493 (5)*	*I(1)*	-2.455 (11)
ρ(National 96 − 100%)	0.89	-2.592 (8)	0.550 (5)*	*I(1)*	-2.182 (8)
ρ(Store 70 − 77%)	0.71	-3.416 (4)*	0.300 (5)*	*I(0)* (JCH)	*NC*
ρ(Store 78 − 84%)	0.43	-3.099 (11)	0.728 (5)*	*I(1)*	-3.414 (10)
ρ(Store 85 − 89%)	1.30	-1.481 (11)	0.536 (5)*	*I(1)*	-2.058 (11)
ρ(Store 90 − 95%)	0.96	-3.073 (7)	0.382 (5)*	*I(1)*	-2.954 (8)
ρ(Other 70 − 77%)	38.25	-2.085 (8)	0.322 (5)*	*I(1)*	-2.120 (8)
ρ(Other 78 − 84%)	20.62	-3.076 (11)	0.609 (5)*	*I(1)*	-3.456 (7)
ρ(Other 85 − 89%)	11.30	-4.202 (7)*	0.174 (5)*	*I(0)* (JCH)	*NC*
ρ(Other 90 − 95%)	20.36	-3.917 (11)*	0.0623 (5)	*I(0)*	*NC*
ρ(Other 96 − 100%)	1.76	-1.747 (8)	0.667 (5)*	*I(1)*	-2.605 (11)
10 percent critical values		-3.130	0.119	(-3.391, 0.114)	-5.727

Asterisk (*) denotes rejection of the null at the 0.10 significance level.

[a] The test statistics (τ_t) of the null hypothesis of *I(1)* are the augmented Dickey-Fuller (1979) (ADF) *t*-statistics of the coefficient on the lagged level variable in the regression of the first-differences on a constant, a time trend, the lagged level, and lagged differences of variables appended to the regression. The number of lags of first differences is reported in parentheses and determined by *R 2.10.1*.

[b] The test statistics (η_t) of the null hypothesis of *I(0)* are the Kwaitkowski, Phillips, Schmidt, and Shin (1992) (KPSS) *t*-statistics. The *t*-statistics are sums of the squared partial sums of residuals divided by an error variance estimator. The residuals are computed from a model in which the series is regressed on a constant and a time trend, and the error variance estimator is a Bartlett kernel weighted-sum of auto-covariances, with the automatic bandwidth parameter reported in parenthesis.

[c] Inferences based on the joint confirmation hypothesis (JCH) of a Unit Root are used when the ADF and KPSS tests conflict (Silvestre, Rossello, and Ortuno 2001). The joint critical values of (-3.391, 0.114) represent the critical values for 300 observations for the ADF and the KPSS with trend. They are interpreted as follows. If the value of the ADF statistic is less (greater) than -3.391 and the value of the KPSS statistic is less (greater) than 0.114 then the series is considered (at the 0.90 level) stationary (nonstationary). Otherwise, the series cannot be confirmed to be a unit root and is therefore considered stationary.

[d] The test statistics (T_k) of the null hypothesis that the *k*th relative price and the vector of composite group prices are not cointegrated are augmented Dickey Fuller tests of *I(1)* residuals from regressing the *k*th relative price on each of the four integrated group price indices. The number of lagged first difference residuals included (in the residual regression) is reported in parenthesis, and is determined by *R* 2.10.1. The 0.10 critical values reported for the individual tests are based on 273 observations and eleven integrated explanatory variables, so that *k*=12 in MacKinnon (1996).

Table 6. Lean Percentage Level Compensated Price and Expenditure Elasticities

Elasticity of the quantity of	With respect to the price of					With respect to
	70 - 77%	78 - 84%	85 - 89%	90 - 95%	96 - 100%	Expenditure
70 - 77%	-0.439*	0.044	0.105*	0.287*	0.004	1.223*
78 - 84%	0.082	-0.509*	-0.010	0.424*	0.013	0.759*
85 - 89%	0.304*	-0.016	-0.869*	0.548*	0.033*	0.791*
90 - 95%	0.505*	0.395*	0.332*	-1.290*	0.059*	1.001*
96 - 100%	0.077	0.153	0.245*	0.726*	-1.201*	0.484*

Asterisk (*) indicates the elasticity estimate is significant at the 5% level.

Table 7. Brand Type Compensated Price and Expenditure Elasticities

Elasticity of the quantity of	With respect to the price of				With respect to
	Local/Regional	National	Store	Other	Expenditure
Local/Regional	-4.550*	0.077	0.931	3.542*	0.291
National	0.028	-2.199*	0.306*	1.865*	0.743*
Store	0.400	0.363*	-2.420*	1.656*	0.752*
Other	0.038*	0.055*	0.041*	-0.133*	1.021*

Asterisk (*) indicates the elasticity estimate is significant at the 5% level.

Table 8. Results of Weak Separability Tests

Utility Tree	Number of Restrictions	*LR*	LR_0	Critical Value[a]
1	134	3726.560	3545.408	174.996
2	129	22621.600	21533.490	169.278

[a] The level of significance is 0.01.